

**The Validity of the Higher-Order Structure of Effortful Control as Defined by Inhibitory Control,
Attention Shifting, and Focusing: A Longitudinal and Multi-Informant Study**

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Abstract

Objective. Effortful control (EC) has been conceptualized as a higher-order construct defined by a class of self-regulatory mechanisms. However, the developmental higher-order structure of EC has seldom been investigated with a thorough psychometric analysis. To begin to fill this gap in the literature, data were obtained from parents and teachers of 185 children (age at T1: $M = 9.43$ y/o, $SD = 1.17$) every two years for eight years. **Method.** We used a structural equation modeling approach for assessing if EC develops as a higher-order factor superordinate to three commonly studied self-regulatory mechanisms, namely inhibitory control (IC), attention focusing (AF) and attention shifting (AS). **Results.** Results showed that (a) IC, AF, and AS followed a similar pattern of growth, (b) EC displayed an acceptable degree of scalar longitudinal invariance when operationalized as a latent variable indicated by IC, AF, and AS, (c) a higher-order structure explained the co-development of IC, AF, and AS, and (d) stability and change in EC negatively predicted externalizing symptoms, much better than the stability and change of IC, AF, and AS, but only for parents' reports. **Conclusion.** Overall, the higher-order structure of EC was supported, but our results also indicated that there is a certain degree of uniqueness in its facets.

Keywords: effortful control, self-regulatory mechanisms, longitudinal structural equation modeling, higher-order latent growth curve models, multi-informant study

The Validity of the Higher-Order Structure of Effortful Control as Defined by Inhibitory Control, Attention Shifting, and Focusing: A Longitudinal and Multi-Informant Study

Effortful control (henceforth labeled EC) is defined as the ability to inhibit a dominant response in order to perform a sub-dominant response (Rothbart & Bates, 2006; Simonds et al., 2007) and includes the abilities “to willfully or voluntarily inhibit, activate, or change (modulate) attention and behavior, as well as to executive functioning tasks of planning, detecting errors, and integrating information relevant to selecting behavior” (Eisenberg et al., 2016, p. 458; also see Eisenberg, 2017; Nigg, 2017). It is the top-down *self-regulatory* component of temperament and, hence, dispositional; moreover, it is believed to contribute to some aspects of personality such as conscientiousness and agreeableness (e.g., Caspi & Shiner, 2006; Eisenberg et al., 2014). EC has been differentiated from less voluntary, or *reactive*, control-related processes (Derryberry & Rothbart 1997; Eisenberg et al., 2013; Pallini et al., 2018; Rothbart & Bates, 2006; Valiente et al., 2013).

Since its introduction (Rothbart, 1989a, 1989b), EC has represented one of the most studied constructs in development psychology, mostly because of its apparent broad role in key areas of children’s development, such as emotional self-regulation, moral development (e.g., empathy and prosocial behaviors), adjustment, and social competences (see Eisenberg et al., 2016, for a review). From a psychometric point of view, it is conceived as a higher-order construct (e.g., Sulik et al., 2010), influencing a set of lower-level distinct – but related – *self-regulatory capacities* (Kochanska, Murray, & Harlan, 2000, p. 220; Rothbart, Ahadi, Hershey, & Fisher, 2001), such as inhibitory control, attention shifting, and attention focusing (e.g., Eggum-Wilkens et al., 2016).

According to Derryberry and Rothbart (1988, p. 966; see also Eggum-Wilkens et al., 2016, p. 544; Rothbart et al., 2001, p. 1406), *inhibitory control* (henceforth IC) represents the ability to inhibit or suppress a pleasurable behavior (e.g., to play with a toy) under instruction or when one is motivated to act, as well as the ability to resist to the execution of inappropriate approach tendencies. *Attention shifting* (henceforth AS) taps the ability to intentionally transfer attention from

one stimulus to another. Conversely, *attention focusing* (henceforth AF) refers to the ability to keep attention on a stimulus, thereby resisting unintentional shifting to irrelevant or distracting stimuli. In this paper, we address if there is a higher-order structure of EC, focusing to the aforementioned three lower-order indicators (namely, the dimensions of IC, AS, and AF) and using a longitudinal and multi-informant sample of 185 children in grades 2 to 5, assessed for five waves every two years (i.e., across eight years). Specifically, our goal was to provide an in-depth psychometric analysis of the validity of the hypothesized developmental higher-order structure of three lower order components of EC in order to examine whether a higher-order model of EC was supported by means of a proper statistical model (Isiordia et al., 2017; Isiordia & Ferrer, 2018). Note that the activation control component of effortful control was not assessed in this study because no such scale was available for the age group when the study was initiated. Thus, our conclusion should be considered limited to a conceptualization of EC as assessed by these three components only, although we henceforth refer generally to “the structure of EC.” That said, we would argue that if IC, AS, and AF behave as mere expression of EC, then researchers are justified in restricting their attention to it. Otherwise, focusing on specificities in the change of the subcomponents may offer insights on the development children’s self-regulation.

Effortful Control as a Second-Order Construct

A review by Nigg (2017) highlighted the close relations among EC, executive functioning, and cognitive control, in particular by summarizing their shared cognitive and physiological concomitants (see Eisenberg, 2017, for a further discussion). These results are mimicked by findings from factor analytic studies that assessed effortful control (henceforth labeled as EC) through questionnaires and/or tasks. These studies typically support the presence of a higher-order latent factor that includes attentional and inhibitory control (Murray & Kochanska, 2002; Rothbart et al., 2001) and remains invariant across gender and ethnicity (Sulik et al., 2010). When researchers have found two separate factors for EC in factor analyses or that aspects of EC differentially predicted children’s behavior, they often had studied “hot” aspects of EC (e.g., delay-

of-gratification tasks in which children had to inhibit their approach to a reward; Kim et al., 2013) or aspects of executive functioning that are not usually included in measures of EC (e.g., working memory, cognitive flexibility; Friedman et al., 2008; Latzman & Markon, 2010). However, some researchers have found that even “hot” and “cold” (top-down processes that operate in more affectively neutral contexts) aspects of EC load on a single factor (e.g., Allan & Lonigan, 2011; Eisenberg et al., 2014). In the present study, only cold aspects of EC were examined.

Also consistent with the view that various sub-aspects of EC load on a secondary factor, several researchers have found significant covariances among IC, AS, and AF. For example, in a sample of 42-month-old children, Eggum-Wilkens and colleagues (2016) found significant and positive correlations ranging from $r = .20$ ($p < .01$; correlation between AS and AF) to $r = .51$ ($p < .001$; correlation between IC and AS). Likewise, among undergraduates, Derryberry and Rothbart (1988) reported correlations ranging from $r = .21$ ($p < .01$; the correlation between IC and AF) to $r = .54$ ($p < .001$; correlation between AS and AF). Other studies, with different samples, reported similar (e.g., White et al., 2011) or higher (i.e., from $r = .33$ to $r = .83$; Eisenberg et al., 2003) sizes of correlations. According to this pattern of correlations, it seems likely that EC is the higher-order construct that accounts for the shared variance of IC, AS, and AF. The above findings support the validity of the conceptual view of EC as a higher-order construct that is superordinate to voluntary, self-regulatory sub-mechanisms.

Most researchers who have studied EC have investigated attentional and behavioral mechanisms separately by using them to construct an overall composite score, or as separate indicators on a latent construct. To our knowledge, no previous study (except for some cross-sectional factorial analyses: Murray & Kochanska, 2002; Rothbart et al., 2001; Sulik et al., 2010) addressed in depth the psychometric validity of the hypothesized higher-order structure, especially from a longitudinal perspective. This is surprising given the frequent use of higher-order models of EC by developmental scientists (Isiordia et al., 2017; Isiordia & Ferrer, 2018). Indeed, as suggested by Isiordia et al. (2017), when “multiple [...] processes are theorized to stem from a common

“cause” or factor, then a statistical model that matches this theoretical model warrants consideration” (p. 1017). Thus, the aim of the present study was to examine the validity of the hypothesized higher- order structure of EC from a developmental perspective. This is accomplished by investigating if it is reflected (or not) in the joint development of its subcomponents. Based on the statistical framework for studying the co-development of correlated psychological constructs proposed by Duncan, Duncan, and Strycker (2006), we hypothesized that if EC represents the shared mechanism explaining the tendency of IC, AF, and AS to exhibit the same level of functioning across individuals and across ages, then the development of these sub-facets should fit well with a common causal factor simultaneously driving their development.

Conceptual Models of the Development of EC and its Lower-Order Components

The studies reviewed above provided evidence for EC as a second-order construct defined by IC, AS, and AF, but findings are limited to the factorial structure at the cross-sectional (concurrent) level. This is problematic because concurrent studies cannot examine similarity in the pattern of change shown by lower-order components, which is a key developmental expectation of second-order constructs. In other words, if some variables are hypothesized to be the lower-order components of a higher-order construct, then they should show a substantial degree of overlap in their change over time. In this regard, we can delineate three possible scenarios (Figure 1-3), each with important, but distinct, theoretical implications, and corresponding to a specific psychometric model of development introduced by Duncan and colleagues (see Duncan et al., 2006).

In the conceptual model shown in Figure 1, IC, AS, and AF are cognitive structures characterized by synchronous and highly interdependent developmental processes. This model is formally known as the associative latent growth model (Duncan et al., 2006, p. 66) or *parallel process model* (PPM; Wickrama et al., 2016). Figure 1 (PPM) offers a graphical representation and the theoretical explanation of this scenario. In this model, there is no higher-order structure of EC. IC, AS, and AF are expected to follow similar, and correlated, trajectories. However, there is not an underlying expression of EC disposition. In this scenario, children are expected to change at an

approximatively similar rate on each of the three constructs. Differences in growth rate are, however, still possible, given that the developmental forces driving the development of each construct are distinct. Thus, it is possible, considering a specific time window, that a child shows greater increases in the abilities to shift or focus his/her attention, while exhibiting a lower capacity to inhibit behaviors.

Figure 2 depicts EC as a higher-order developmental mechanism explaining the observed synchronism in the development of IC, AS, and AF. This model is formally known as the *factor of curves model* (FCM; Duncan et al., 2006; Wickrama et al., 2016). EC as a latent mechanism can be conceptualized, as usual, as the overall individual EC capacity (Wang, Eisenberg, & Spinrad, 2019). Change in the higher-order EC construct – represented as the common intercept and the common slope in Figure 2 – drive changes in its lower-order components by determining the level and the shape of their trajectories (see Bollen, 1989). The developmental meaning of the model is, thus, that the development of IC, AS, and AF is expected to be mostly determined by development in the latent EC disposition, with a little room for asymmetries in development represented by their residual components. From a practical point of view, children are expected to show the same growth rate, whatever it might be, on each of the three EC indicators resulting from the effect of EC.

In a third – and final – scenario, IC, AS, and AF are reduced to the status of within-time temporal indicators of EC; the construct of EC at each time represents what these three competences have in common within each time point (and across time if looking for longitudinal invariance of the latent construct). This model is formally known as the *curve of factors model* (CFM; Duncan et al., 2006; Wickrama et al., 2016), and it is similar to latent construct models with multiple indicators of EC typically used in longitudinal research. Figure 3 (CFM) offers the statistical representation and a brief explanation of this scenario. In this scenario, only the EC developmental trajectory is of interest because changes in IC, AS, and AF, as observed at a specific time point, are jointly determined by changes in EC. Thus, IC, AS, and AF are not allowed to have

specific trajectories (as in the previous scenario). The three facets are indicators of EC and are expected to be equivalent in that regard across time (i.e., longitudinally invariant). The point of interest in this model is if these indicators are equivalent (and to what degree) indicators of EC at each of the five time points. The strong causality assumption contained in this model (i.e., variations in the lower-order components are determined by the higher-order EC) is directly shared with the single time point, higher-order cross-sectional model, often used to operationalize the construct of EC in empirical studies (Sulik et al., 2010; Wang, Eisenberg, & Spinrad, 2019). In this scenario, in order to evaluate the development of a child's self-regulatory abilities, one would simply look at change occurring in an overall measure of EC, not change in the indicators.

Current Evidence on the Development of Effortful Control Lower-Order Components

In order to provide a preliminary evidence relevant to our three scenarios, we review the evidence in available longitudinal studies that investigated the development of EC subcomponents. This review of longitudinal studies suggests that the lower-order components of EC track similar trajectories, but with some important differences. During early childhood, all three facets (IC, AF, and AS) tend to increase in a similar way (Moilanen et al., 2010; Ruff & Capozzoli, 2003; Santillán & Khurana, 2018; Willoughby et al., 2012).

In contrast, during late childhood, IC, AF, and AS follow different trajectories: IC and AS slightly tend to increase (Murphy et al., 1999; Troller-Renfree et al., 2019), whereas AF remains stable (Murphy et al., 1999; Zhou et al., 2007). Even in adolescence, IC, AF, and AS show divergent trajectories (Atherton, Lawson, & Robins, 2020): IC tends to increase across the adolescence, whereas both AF and AS (in their study, conceptualized in a combined fashion as Attention Control) decrease. Overall, this pattern of change seems to agree more with a parallel process model (i.e. first scenario) or with a factor of curves model (i.e. the second scenario, in which three synchronous growth factors are jointly determined by a higher-order intercept and slope representing latent EC), rather than with a curves of factors model (i.e. the third scenario, with a single intercept and a single slope determining the higher-order EC factors).

Most studies examine the development of EC, without evaluating the development of IC, AS, and AF. These studies generally suggest that the increase of EC during the period from early to late childhood is not linear. During preschool age (especially up to 5-6 years), global EC develops substantially (Kochanska et al., 2000; Lengua et al., 2015; Li-Grining, 2007), whereas in elementary school, its development decelerates and continues more slowly, with a higher degree of stability (up to about 11 years; Atherton, Lawson, & Robins, 2020; King et al., 2013; Murphy et al., 1999). During early adolescence (from about 12 to 14 years), EC slightly decreases and then increases again during late adolescence to young adulthood (16 years and over; Atherton, Lawson, & Robins, 2020; Leon-Carrion et al., 2004). Of course, these studies are based on the implicit assumption that the third scenario reviewed above is the best fitting one, a point we are going to investigate in this study.

External Validity of Effortful Control

Another important consideration is in regard to the predictive validity of EC. If a higher-order structure is the better model (as above studies would suggest), then EC is expected to (generally) show incremental validity compared to its lower-order components (see Edwards, 2001), and thus might be expected to predict other related aspects of functioning better (or not) than the lower-order elements. In this regard, we note that although numerous studies have demonstrated the predictive validity of EC, its incremental predictive value in comparison to IC, AF, and AS considered individually has not been clarified.

Previous empirical studies have documented associations between EC and indicators of adjustment/maladjustment, such as behavioral problems, peer acceptance, and school achievement (see Eisenberg et al., 2010; Eisenberg et al., 2016, for reviews). Specifically, EC negatively predicts aggressiveness (Crockenberg et al., 2008), school behavioral problems (Atherton et al., 2019; Sawyer et al., 2015), and externalizing behaviors (Eisenberg et al., 2009; Olson et al., 2005; Schoppe-Sullivan et al., 2009; Valiente et al., 2003). Likewise, in a recent study using data from a large sample of Mexican-origin youth, Lawson and colleagues (in press) found concurrent and

longitudinal negative associations between EC and depression, ADHD, antisocial interpersonal functioning and school discipline, and concurrent and longitudinal positive associations between EC and school grades. Notably, children with lower EC abilities tend to experience more externalizing problems, in both preschool and school years, probably because they are less able to inhibit their behavior and manage anger and frustration, and, thus, they react more to adverse events (Atherton, Lawson, Ferrer, & Robins, 2020; Eisenberg et al., 2010).

Issues relating to the incremental validity of EC compared to its lower-order dimensions can be framed under the longitudinal framework delineated above, and in particular into one of the respective three general proposed developmental scenarios. Specifically, if IC, AS, and AF operate as different, but correlated, constructs across developmental ages (scenario 1; see Figure 1), it is likely that they show some possibly different prediction and, consequently, the three facets together predict developmental outcomes such as externalizing problems better than a second-order construct of EC. In contrast, if changes in the developmental trajectories of IC, AS, and AF are due to change in higher-order EC (scenario 2 and 3; see Figure 2 and 3, respectively), it is then of interest to investigate if there is different prediction by the higher-order mechanism explaining their development (i.e., changes in EC), and any residual change component (i.e., intercept or slope) of the three lower-order constructs. In this model, if IC, AS, and AF represent the mere expression of EC at each time point, no incremental validity is expected from them, over and above that predicted by EC.

The Present Study

The aim of the present study was to provide data that address how we might best conceptualize the construct of EC. In particular, we sought to investigate whether EC is an overarching developmental latent factor accounting for the shared variance in the temporal manifestations and in the development of IC, AS, and AF. Thus, the research questions we aimed to answer were “Do IC, AS, and AF show a similar developmental course?” (Research Question 1), “Is the co-development of IC, AS, and AF better explained by a common higher-order structure?”

(Research Question 2), and “Does the development of the higher-order structure outperform the development of single components in the prediction of externalizing symptoms?” (Research Question 3). In doing so, we used a multi-informant and longitudinal sample of elementary school children rated by parents and teachers at five assessments, each two years apart. We used measures of IC, AS, and AF gathered in five different occasions in order to estimate and compare the fit of the three alternative developmental models described above, and corresponding to scenarios 1 to 3. If EC is a higher-order construct at the core of IC, AS, and AF as described in scenarios 2 and 3, these models should best fit the data. Moreover, we hypothesized that EC intercept and slope would outperform those of the lower-order sub-facets of EC when predicting externalizing symptoms across time. This expectation was based on the idea that EC represents the developmental core of IC, AS, and AF. We choose externalizing symptomatology as the external outcome because the negative relation between EC and externalizing symptoms is one of the more consistent findings in the developmental research (e.g., Eisenberg et al., 2005, 2010, 2016; Valiente et al., 2003).

To summarize, the present study was designed to test four hypotheses. Given that researchers have speculated that IC, AS, and AF show similar developmental trajectories because they are driven by a common higher-order structure (EC), we hypothesized that EC sub-mechanisms would follow a similar pattern of growth in terms of mean-level change and mean-level variance (*Hypothesis 1*); parameters linking EC to its sub-mechanisms are invariant across time (*Hypothesis 2*); the co-development of IC, AS, and AF is better explained by imposing a higher-order structure (*Hypothesis 3*); and the development of the higher-order structure outperforms the development of single components in regard to the prediction of externalizing symptoms (*Hypothesis 4*).

Method

Participants¹ and Missing Data Consideration

Participants were in a longitudinal study begun two years prior to Time 1 (T1); initially, there were 199 children in grades kindergarten to third grade. Children were assessed five times, every two years. Sometimes data were available at some later assessments but not some earlier ones, resulting in 185 children participating at one or more assessments. The minimum size of retention rate was 75.03% for parents' ratings and 50.94% for teachers' ratings. Hence, for the total number of children assessed in our study (185), at T1 in this study (2 years after the initiation of the study), children's ages ranged from 88 to 149 months ($M = 9.43$, $SD = 1.17$); 94 were females (50.8%) and 91 were males (49.2%). At T1, data were available from 166 parents (89.73%²) and 159 teachers (85.95%); at T2, from 168 parents (90.81%) and 148 teachers (80%); at T3, from 157 parents (84.86%) and 135 teachers (72.97%); at T4, from 142 parents (76.76%) and 126 teachers (68.11%); and at T5, from 125 parents (67.57%) and 81 teachers (43.78%). The children were predominately from Caucasian, middle-class families in suburbs of a larger U.S. southwestern city (81.1%); 9.7% were Hispanic; 1.6% were African-American; 2.2% were American Indian; 0.5% was of Asian origin; and 4.9% were of mixed origin.

In order to control for the possibility that missingness was caused by one of the study variables, we ran an omnibus (i.e., we imputed all study variables, for both informants, in one analysis) Missing Completely at Random (MCAR) Little's test (Enders, 2010). This test demonstrated that the data were consistent with the assumption of being MCAR, given the nonsignificant size of the resulting chi-square statistic ($\chi^2 = 2745.96$, $df = 2712$, $p = .320$)³. Thus, Full Information Maximum Likelihood was used to handle missing data in all subsequent analyses.

¹ There are numerous papers published using this data set, too many to list (e.g., Eisenberg et al., 1996, 1997). But none of those involved any analyses of this sort. One paper that looked at developmental trajectories included data from fewer time points and combined data from this sample with data from another sample (Zhou et al., 2007).

² Percentages refer to the total number of children (i.e., 185).

³ In order to test whether the sample at our T1 was different than the sample collected two years before (henceforth T0, which was excluded because of some differences in data collection such as the lack of inhibitory control items), we ran a series of analyses. Results suggested that the samples are not different in terms of sex, age, parents' education, and income.

Finally, given that teacher-reported externalizing symptoms (assessed at T5) had a high missingness rate (55.1%), we imputed missing values by means of the *imputeLearner()* function (because in the case of LASSO regression FIML can't be used) from *mlr* package (Bischl et al., 2016), using a regression learner ("*regr.rpart*"; see Rhys, 2020, p. 220-221).

Procedure

At T1 to T4, primary parents' reports of effortful control and externalizing were obtained when they came to the laboratory; scheduling was as close to two years apart as possible. However, a relatively small number of parents could not come to the laboratory (e.g., had moved or were unavailable) and completed questionnaires by mail. Moreover, at T5, all data were collected by mail. With parental and school permissions, teachers were sent questionnaires at all five assessments that they returned by mail. Parents and teachers were paid for completing surveys. All procedures were approved by [Blinded] Institutional Review Board.

Measures

Effortful control. All items included in this study were from the Children's Behavior Questionnaire (CBQ; Goldsmith & Rothbart, 1991; Rothbart et al., 1994; Rothbart et al., 2001); scales had to be available at all assessments (which is why we did not use the first assessment of the larger longitudinal study). Items⁴ were rated on a 7-point scale ranging from 1 (*extremely untrue*) to 7 (*extremely true*). For both parents and teachers, *inhibitory control* was measured by 13 items, of which 9 were not reversed (e.g., "*Can lower his/her voice when asked to do so*") and 4 were reversed (e.g., "*Has a hard time following instructions*"). *Attention shifting* was measured by 11 items, of which 3 were not reversed (e.g., "*Can easily shift from one activity to another*"), and 8 were reversed (e.g., "*Often doesn't hear me when she/he is working on something*"). *Attention focusing* was measured by 12 items, of which 5 were not reversed (e.g., "*When picking up toys or*

⁴ The attention shifting scale was from an early version of the CBQ (Goldsmith & Rothbart, 1991) but was dropped from later versions by the scale's original authors. It is retained here because we used the original version of the attention scales.

other tasks, usually keeps at the task until it's done") and 7 were reversed (e.g., "*Has trouble concentrating when listening to a story*"). Some CBQ items were changed slightly (e.g., a few words) to fit the classroom context or to be appropriate for an older age group. Although four items from the inhibitory control scale were used infrequently by teachers and dropped in some prior papers using this data set, all items were retained in analyses but adults' reports on a scale were retained only if they responded to at least 70% of the items on the scale. Given that no teacher responded to less than 70% of items for each scale, the sample sizes for teachers are those reported in "Participants and Missing Data Consideration." As showed in Table S1 of the Supplementary Materials, Cronbach's alphas ranged from .74 to .91.

Externalizing symptoms. Externalizing symptoms were assessed at T5 by via 23 items gathered from the *Child Problem Behavior Checklist* (Lochman & Conduct Problems Prevention Research Group, 1995). Teachers and parents were asked to report how often a child engaged in a series of externalizing behaviors (e.g., "*Argues*", "*Disobedient*", "*Threatens or bullies peers*") on a 4-point Likert scale ranging from 1 (*Never*) to 4 (*Often*). Cronbach's alphas for parent- and teacher-rating scale were .94 and .95, respectively.

Data Analytic Strategy

To investigate whether our hypotheses were tenable, we used a longitudinal structural equation modeling approach (Little, 2013; McArdle, 2009). First, we probed the shape of change for each EC facet separately (IC, AS, and AF) by using different univariate Latent Growth Curve Models (LGCM; Bollen & Curran, 2006; Grimm et al., 2017; Meredith & Tisak, 1990) with random factor loadings (e.g., Sallquist et al., 2009), in order to take into account age variability at each time-point (McNeish & Matta, 2020). These models allowed us to investigate the development of a construct by using different parametrizations of change (no-change, linear, quadratic) and to address the issue of whether the three facets of EC show similar patterns of development. These models allowed investigate several characteristics of the development of the construct of interest through the inspection of five parameters of change. Mean (κ_1) and variance (ϕ_{11}) of the latent

variable “intercept” represent the mean of the construct and its between-individual variance at a specific time point (usually T1), respectively. Mean (κ_2) and variance (ϕ_{22}) of the latent variable “slope” represent the direction and quantity of change across time points and the degree to which it varies between individuals, respectively. Finally, the covariance between intercept and slope (ϕ_{12}) represents the degree to which a specific time point (usually T1) and the change covary.

In order to investigate the longitudinal measurement invariance of composite scores representing EC, a condition assumed by latent growth models (see Meredith & Tisak, 1990), we started by testing *configural invariance*, simply assuming that the same observed variables (IC, AS, and AF) loaded onto the same latent variable (EC) across time. Then, we moved to *metric invariance*, and tested the assumption that factor loadings did not vary significantly in their size across time. Then, we examined *scalar invariance*, in which we tested the assumption that intercepts did not vary significantly in their size across time. *Partial scalar invariance* was calculated when not all of the intercepts could be fixed to be equal across time.

Third, to investigate whether the co-development of IC, AS, and AF is better explained by a higher-order structure (Isiordia et al., 2017; McArdle, 1988; Wickrama et al., 2016), we specified three models, namely (a) the *parallel process latent growth curve model* (PPM), where intercepts and slopes of IC, AS, and AF covaried (see Figure 1); (b) the *factor of curves model* (FCM), in which a higher-order intercept and a higher-order slope (that for EC) accounted for the shared variance of the three intercepts and the three slopes, respectively (see Figure 2); and (c) the *curve of factors model* (CFM), in which one intercept and one slope accounted for the development of EC, which was assessed at each time point as a latent variable composed of IC, AS, and AF (see Figure 3). Although PPM is a simple multivariate latent curve model, CFM and FCM are both considered higher-order latent curve models. A better fit of CFM and FCM than PPM would provide support for a higher-order structure that accounts for the shared development of the constructs under examination.

Fourth, in order to investigate the (longitudinal) construct validity of EC as measured by individual facets or a higher-level construct of EC, we proceeded as follows. First, we extracted factor scores of the intercept and slope from each of the four best-fitting longitudinal models⁵ in order to obtain 8 observed variables. Then, we ran a series of regressions for estimating the degree to which stability (intercept) and change (slope) of IC, AS, and AF, and EC predicted externalizing symptoms, after controlling for age and gender.

Statistical Analyses

Mplus 8 statistical software (Muthén & Muthén, 1998-2017) was used to estimate all structural equation models and to handle missing data, using the Full Information Maximum Likelihood (FIML) estimator. In contrast, regularized regressions were run with *glmnet* (Friedman et al., 2010) and *glmnetUtils* (Ooi, 2020) packages in R (Version 4.0.3; R Core Team, 2020). The model comparison for all growth models (first- and second-order) was evaluated using the difference in Bayesian Information Criteria (BIC), given that common fit statistics are not defined for individually varying age-based models (this is because factor loadings are random effects; Muthén & Muthén, 1998-2017). Measurement invariance models were instead compared by using the likelihood ratio test ($\Delta\chi^2$) and difference in CFI (ΔCFI), given that they do not require the estimation of random effect factor loadings. Based on previous literature on measurement invariance (Cheung & Rensvold, 2002; Little, 2013), we considered the step of invariance tenable when $\Delta\chi^2$ was not significant ($p > .05$) and $\Delta\text{CFI} < .010$.

Finally, we ran a series of regularized regressions (with 10-fold cross-validation) for estimating the degree to which the model estimated values of stability (intercept) and change (slope) of IC, AS, AF, and EC entered together in the model predicted externalizing symptoms, after controlling for age and gender. We used L1 regularization (i.e., LASSO), which is appropriate in presence of a high degree of multicollinearity among predictor variables and when the aim is to find

⁵ Three best fitting first-order LGMs (for IC, AS, and AF) and one best fitting higher-order LGM (for EC).

best predictors of a specific outcome, given that L1 regularization shrinks to zero the effect sizes of non-relevant variables for prediction (e.g., McNeish, 2015). Estimated parameters (e.g., regression coefficients and R^2) were extracted from the model with the lambda hyperparameter⁶ fixed to the largest value of lambda such that the error was within 1 standard error (i.e., *lambda.1se* in *glmnet* package language), as suggested by literature (e.g., Zume & Mount 2020).

Results

Descriptive Statistics

Descriptive statistics, separated for parents and teachers, are reported in the Supplementary Materials (Table S1). Each composite score (calculated by averaging its respective items) showed only a slight degree of departure from normality; indeed, all indices of skewness and kurtosis were $< |1|$. All correlations were positive: most of them were significant ($p < .05$), indicating substantial relations among constructs. The mean of the cross-sectional correlations among IC, AS, and AF control were .46 (T1), .48 (T2), .45 (T3), .54 (T4), .53 (T5) for parents, and .66 (T1), .72 (T2), .70 (T3), .77 (T4), .70 (T5) for teachers. The cross-sectional means of inter-rater correlations (not reported in Table S1) were .44 ($SD = .03$) for IC, .26 ($SD = .04$) for AS, and .41 ($SD = .08$) for AF.

Univariate Latent Growth Curve Models

As shown in Table 1, the model that generally best represented the development of IC, AS, and AF was the linear growth model⁷. That said, one can reasonably conclude that IC, AS, and AF exhibited quite similar developmental patterns across time (see plots in Figure 4).

Next, we explored parameters of change. As shown in Table 1 (see rows corresponding to “first-order level”), all six models (three facets of EC for two reporters) had an intercept with a

⁶ The lambda (λ) hyperparameter sets the degree of penalization in regularized regression. For instance, setting $\lambda = 0$ the regression is not regularized, and results correspond to those obtained with classical OLS estimation. The higher the lambda, the more the penalty function shrinks toward zero regression coefficients. Given that it is difficult to decide what is the appropriate value for lambda, *glmnet* estimates parameters by using different values of lambda. Hence, researchers can choose the value for lambda based on cross-validation results: For example, one may extract parameters from the model that gives minimum mean cross-validated error (*lambda.min*) or, as in the present case, from the model which error is within one standard error of the minimum (*lambda.1se*).

⁷ Before running latent growth models, we investigated measurement invariance for all study variables (IC, AF, AS). All constructs reached scalar invariance. Results are reported in Appendix (Table S3).

significant mean (κ_1) and significant variance (φ_{11}); this finding indicates a substantial degree of between-child variability at T1 for all the study variables as well as across informants. In regard to change, for all the study variables and across informants, the mean of the slope (κ_2) was positive, and in only one out of six models was it nonsignificant (κ_2 of AF reported by parents). Slope variances (φ_{22}), assessing between-child variability in their longitudinal change, were all significant except for teacher-reported AF. Overall, these findings support our hypothesis regarding the same direction of change shared by IC, AS, and AF. In sum, above results supported *Hypothesis 1*.

Measurement Invariance

Results for the measurement invariance analysis are presented in the Supplementary Materials (Table S2). The configural models for both parents' and teachers' reports had a good fit to the empirical data. Moreover, the nested models (evaluated with $\Delta\chi^2$ and ΔCFI) indicated that both metric invariance models (equal factor loadings across time) were tenable. In addition, the imposed constraints on factor loadings did not significantly worsen the configural models. Finally, scalar invariance (equal intercepts across time) was tenable for parents but showed a slight degree of misfit in teachers ($\Delta CFI = .010$). Therefore, through inspection of modification indices, we freed one intercept (the intercept of AF at T3), resulting in partial scalar invariance. Thus, we can conclude that EC showed an acceptable degree of longitudinal measurement invariance when operationalized as a latent variable composed of IC, AS, and AF. This finding supports the view that the relations between EC and their hypothesized facets were consistent across time, which is important for computing second-order models. In sum, above results supported *Hypothesis 2*.

Comparison of Multivariate LGCM and Higher-Order LGCM

After establishing that IC, AS, and AF followed a similar pattern of growth, had the same direction of change, and their relations with EC were invariant across time, we moved forward to probe their co-development over time. As shown in Table 1 (see rows corresponding to "second-order level") the lower BIC for both parents and teachers was showed by the FCM

In regards to parameters of change (see Table 1), the main results were that (a) EC had substantial between-individual variance at T1, (b) the average level of EC at T1 was very similar across informant, and (c) EC showed significantly positive growth across time.

Overall, these findings support the validity of the higher-order structure of EC, which can be considered a process that substantially takes into account the co-development of IC, AS, and AF. Furthermore, based on information criteria, we found that the best fitting higher-order LGCM was the FCM. Accordingly, from a developmental perspective, EC seems to act as a shared developmental mechanism producing the observed synchrony in the development of EC sub-facets (IC, AS, and AF) that remain separate but strongly interconnected developmental constructs. In sum, above results supported *Hypothesis 3*.

Construct validity

Results from LASSO regressions, in which we examined the prediction of externalizing symptoms from the individuals' intercepts and slopes (representing individual starting levels and degree of change on each construct) extracted from the best fitting first- and higher-order longitudinal models, are reported in Table 2. For each reporter (parent and teacher), we ran three models: Model 1 (only intercepts as predictors), Model 2 (only slopes as predictors), and Model 3 (intercepts + slopes as predictors). Results, reported in Table 2, indicate that, for parents' reports, EC's intercept and EC's slope were the best predictors of externalizing symptoms in that they were the only regression coefficients that were not reduced to be zero in any model. In contrast, results from teachers' ratings showed that (a) EC did not predict externalizing symptoms in any model, and (b) the intercept of IC was the strongest predictor. In conclusion, our hypothesis was fully supported by analyses using parents' reports, but not supported by analyses with teachers' reports⁸.

Given that researchers often have computed a composite score combining parent and teacher reports of externalizing, we ran a further analysis in which all predictors described above were used

⁸ We also ran analysis without imputing missing values on teacher-reported externalizing symptoms, but LASSO regression returned all all (shrunked to) zero coefficients.

to predict a composite scores of externalizing symptoms obtained from the average of teachers' and parents' ratings of externalizing symptoms. Results supported the significant predictive effect of (a) the intercept and slope for parent-reported EC, and (b) the teacher-rated IC intercept (see Table 3).

In sum, above results only partially supported *Hypothesis 4*.

Discussion

A number of researchers studying EC seem to assume that it denotes a group of somewhat different self-regulatory mechanisms. However, to our knowledge, no previous study tested the validity of its developmental higher-order structure with current, sophisticated methodological procedures. Thus, in this paper, our aim was to corroborate the validity of the higher-order structure of EC in a longitudinal (5 waves) and multi-informant (parent and teacher raters) sample of elementary children rated five times, once every two years. Results indicate that EC is a construct that significantly accounts for the shared variance of three representative self-regulatory mechanisms, namely IC, AS, and AF. This conclusion was drawn by analyzing results derived from the statistical models specified for testing our hypotheses. Three out of four hypotheses were substantially confirmed. First, all EC sub-mechanisms followed a similar pattern of growth (*Hypothesis 1*). Second, parameters linking EC to its sub-mechanisms showed an optimal degree of invariance across time (*Hypothesis 2*). Third, the development of IC, AS, and AF was highly correlated, and a higher-order structure (i.e., EC) that accounted for their co-development was improved model fit (*Hypothesis 3*). The fourth hypothesis (*Hypothesis 4*), however, was only supported for parents' reports. Specifically, the intercept and slope for parent-reported EC (rather than those for the parent-reported sub-facets) were the strongest predictors of externalizing symptoms; in contrast, the EC intercept and slope for the teacher-report data did not predict externalizing symptoms above and beyond that of the sub-components (i.e., IC). However, it is noteworthy that some of the teachers changed every year and more than half externalizing symptom scores for teachers were missing and thus were imputed: This makes results less accurate than those obtained using parents' ratings. Moreover, given the number of children in classrooms, it is likely

that problems in inhibiting behavior are more salient to teachers than are problems in focusing and shifting attention.

In regard to the development of EC and its facets across time, we found that growth was positive. This finding is consistent with previous longitudinal studies with a similar age range, as reported in literature reviews (Eisenberg et al., 2010, p. 499; Eisenberg et al., 2016, p. 460). However, this change was not constant across all children. Indeed, children show differences in the way they change, as indicated by the significant size of variances for the slopes. Yet, the negative prediction of externalizing symptoms by the slope – despite the differences observed across raters – suggests that the way children change across time in EC mechanisms is as important as differences observed at a single time point (i.e., the intercept). Given the prediction by slopes, the results suggest that it is important to take into account between-person differences in within-person change when the goal is to predict specific functional outcomes.

In regard to the second-order growth structure of EC, we found – across both informants – that a factor of curves model (FCM) fit better than a curve of factors model (CFM). This finding seems to support the idea that IC, AS, and AF are sub-domains of EC that maintain a certain degree of uniqueness. Thus, it seems that EC is a higher-order structure that drives the relation among the developmental trajectories of IC, AS, and AF, but these three sub-mechanisms cannot be considered as simple indicators of EC because they appear to maintain some significant non-shared characteristics in their development in statistical models. This is not surprising given that previous researchers have reported that the components sometimes predict outcomes better than a higher-order construct, depending on what was being predicted (Eggum-Wilkens et al., 2016).

Limitations

The strengths of this contribution include the use of a longitudinal and multi-informant sample and the use of a latent variable framework for conducting our analyses. Nonetheless, there are several limitations that should be noted. Probably, the main conceptual piece missing from the present investigation is the activation control component of effortful control that was not included

in the version of the CBQ used in this study. This component differs from the more traditional “executive-function-like” components of inhibitory and attention control, and it has a distinct developmental trajectory from late childhood to young adulthood compared to the other two facets (see Atherton, Lawson, & Robins, 2020). This exclusion limits the validity of our study to the three component of EC that were considered. Another limitation is the relatively small sample size could produce power-related problems, such as finding non-significant parameters that are significant in the population. Furthermore, in this study, the analyses for parents’ and teachers’ ratings of EC and EC’s facets were kept separate; future studies (with a very large sample size) could use multi-indicator multi-informant latent growth curve models to include all measures in a single model (Geiser et al., 2019). Of importance, in this study, we tested the validity of the higher-order structure of EC only by relying on one measure (the CBQ). Future studies should replicate our findings with other EC measures, such as other questionnaires (Verstraeten et al., 2010) or behavioral and observational measures (for instance, those used in Eisenberg et al., 2005; Valiente et al., 2003; Sulik et al., 2010; Zhou et al., 2007). Finally, our findings should be replicated in samples consisting of a different age range than the one used in our study, and with other cultural and racial/ethnic groups.

Implications and future directions

Overall, our findings have several important implications. First, we found support for a higher-order structure of EC that corresponds to a developmental mechanism explaining the observed synchrony in change exhibited by its lower-order components (e.g., Isiordia et al., 2017). In contrast, the idea that IC, AS, and AF are simple indicators of EC with no common or shared developmental trajectory was not supported. Moreover, although the literature offers several insights for the implementation of higher-order statistical models (in particular for longitudinal data; Alessandri et al., 2013; Geiser et al., 2013; Isiordia et al., 2017; Isiordia & Ferrer 2018; Hancock et al., 2001; McArdle, 1988; McNeish & Dumas, 2017; Wickrama et al., 2016), to our knowledge, no

study outlined the procedures that should be followed for testing the validity of a higher-order developmental construct. This study could be a good starting point.

Second, we would highlight that the validity of a higher-order factor does not by itself justify the use of an observed composite score. Loosely speaking, our findings suggest that it is not optimal to operationalize EC through the use of a composite score computed by the arithmetic mean of IC, AS, and AF. This procedure is detrimental because a unique composite score cannot distinguish between common variance (the shared variance of the sub-mechanisms, which is the real variance of the higher-order construct) and unique variance (which is the variance of each sub-mechanism not related to the higher-order construct). Thus, it seems preferable, when possible, to use a latent variable approach (e.g., Bollen, 1989; Kline, 2016; Little, 2013)⁹.

Although our data supported a higher-order structure of EC, the presence of a higher-order structure should not affect researchers' interest in studying its sub-mechanisms separately. Indeed, our findings highlighted some interesting differences in the development of IC, AS, and AF (see for example the differences in some growth parameters reported in Table 1 and depicted in Figure 4); therefore, the researcher's rationale in studying either the higher-order factor or its sub-mechanisms should be influenced by substantive rather than methodological reasons.

Conclusion

Overall, the aforementioned findings supported the view of EC as a mechanism that drives in a significant way the development of IC, AS, and AF, but at the same time it cannot be considered a "direct proxy" of its lower-order components. At the same time, the data suggest cautious in reducing EC to a "direct proxy" of its lower-order mechanisms. Indeed, our findings also support some uniqueness of IC, AS, and AF that deserves to be addressed both methodologically (e.g., by means of latent variable models) and theoretically (e.g., investigate

⁹ We would point out that the usefulness of studying EC with a latent variable approach is not limited to the points we summarized above. Indeed, Wang, Eisenberg, and Spinrad (2019) highlighted how a latent variable approach (in particular, a bifactor model) is also useful for disentangling the variance of EC with that of other conceptually overlapping constructs (impulsivity, in their study) in order not to confound the unique contribution of each construct in the relation with external variables (ego resilience, in their study).

potential differences across raters). That said, we believe that the present study has the potential to contribute to the literature by offering important insights regarding the structure of EC, as well as hints that can be used for the study of any other higher-order factor pertaining to research on human development.

Declaration of Conflicting Interests

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Data Availability Statement

Mplus and R syntaxes for reproducing analyses are available at

https://osf.io/j8cfv/?view_only=94794d1aaf2e41c0990287833ec04594

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Table 1
Latent Growth Curve Models for Parent-Rating and Teacher-Rating

Level	Variable	Informant	Growth/Model	LL	NFP	BIC	κ_1	ϕ_{11}	κ_2	ϕ_{22}	ϕ_{12}
First-order	Inhibitory Control	P	no-growth	-750.669	7	1537.880					
			linear	-738.432	10	1529.068	5.17***	0.522***	0.024**	0.005**	-0.012 ^{n.s.}
			quadratic	-737.319	14	1547.724					
		T	no-growth	-664.368	7	1364.889					
			linear	-653.728	10	1359.104	5.109***	0.884***	0.036**	0.008*	-0.070***
			quadratic	-652.446	14	1377.198					
	Attention Shifting	P	no-growth	-790.433	7	1617.409					
			linear	-772.086	10	1596.375	4.173***	0.422***	0.037***	0.003*	0.004 ^{n.s.}
			quadratic	-769.960	14	1613.006					
		T	no-growth	-883.615	7	1803.696					
			linear	-873.589	10	1799.272	4.702***	0.564***	0.045***	0.006*	-0.047**
			quadratic	-866.126	14	1805.185					
	Attention Focusing	P	no-growth	-854.882	7	1746.307					
			linear	-842.740	10	1737.684	4.684***	0.649***	0.013 ^{n.s.}	0.007***	-0.010 ^{n.s.}
			quadratic	-840.860	14	1754.806					
		T	no-growth	-887.996	7	1812.458					
			linear	-876.878	10	1805.850	4.672***	0.889***	0.05***	0.003 ^{n.s.}	-0.049*
			quadratic	-874.736	14	1822.405					
Second-order	Effortful Control	P	PPM	-2119.904	57	4537.368					
			FCM	-2129.140	48	4508.858	5.171***	0.492***	0.024**	0.004**	-0.007 ^{n.s.}
			CFM	-2116.869	58	4536.520					
		T	PPM	-1993.561	57	4284.063					
			FCM	-1999.472	48	4248.999	5.090***	0.815***	0.045***	0.004 ^{n.s.}	-0.049**
			CFM	-1999.085	58	4300.321					

Note. In FCM and CFM (for both parent and teacher) we fixed a residual variance of one observed variable to be zero because negative and non-significant (thus, original FCM and CFM should have 49 and 59 number of free parameters, respectively).

LL = Loglikelihood; BIC = Bayesian Information Criterion; NFP = number of free parameters; κ_1 = mean of the intercept; φ_{11} = variance of the intercept; κ_2 = mean of the slope; φ_{22} = variance of the slope; φ_{12} = covariance between intercept and slope; P = Parent; T = Teacher; PPM = Parallel Process Model; FCM = Factor of Curves Model; CFM = Curve of Factors Model.

The best fitting models are reported in bold. Parameters of change (κ_1 , φ_{11} , κ_2 , φ_{22} , φ_{12}) were reported only for the best fitting models.

^{n.s.} $p > .05$. * $p < .05$. ** $p < .01$. *** $p < .001$.

Table 2

Prediction of Externalizing Symptoms from Age, Gender, and Factors Scores of Intercepts and Slopes (LASSO regression)

Model	Predictors	Parents		Teachers	
		Regression coefficient	R^2	Regression coefficient	R^2
1	(Intercept)	1.938		1.450	
	Age	-		-	
	Gender	-		-	
	Inhibitory Control intercept	-		-0.120	
	Attention Shifting intercept	-		-	
	Attention Focusing intercept	-		-	
	Effortful Control intercept	-0.037	0.060	-	0.228
2	(Intercept)	1.936		1.450	
	Age	-		-	
	Gender	-		-	
	Inhibitory Control slope	-		0.089	
	Attention Shifting slope	-		-	
	Attention Focusing slope	-		-	
	Effortful Control slope	-0.084	0.147	-	0.157
3	(Intercept)	1.946		1.450	
	Age	-		-	
	Gender	-		-	
	Inhibitory Control intercept	-		-0.143	
	Attention Shifting intercept	-0.002		-	
	Attention Focusing intercept	-		-	
	Effortful Control intercept	-0.100		-	
	Inhibitory Control slope	-		-	
	Attention Shifting slope	-		-	
	Attention Focusing slope	-		-	
	Effortful Control slope	-0.127	0.333	-	0.250

Note. Model 1 = predictors are intercept factor scores; Model 2 = predictors are slope factor scores; Model 3 = predictors are intercept and slope factor scores.

All predictors but gender were standardized, given that age, intercept factor scores, and slope factor scores had a different metric. The value of ‘ - ’ denotes a regression coefficient pulled toward zero.

Table 3

Prediction of the composite score 'Externalizing Symptoms Parent/Teachers' from Age, Gender, and Factors Scores of Intercepts and Slopes (LASSO regression)

Informant	Predictors	Regression coefficient	R^2
P	(Intercept)	1.701	0.323
	Age	-	
	Gender	-	
	Inhibitory Control intercept	-	
	Attention Shifting intercept	-	
	Attention Focusing intercept	-	
	Effortful Control intercept	-0.050	
	Inhibitory Control slope	-	
	Attention Shifting slope	-0.014	
	Attention Focusing slope	-	
T	Effortful Control slope	-0.040	
	Inhibitory Control intercept	-0.069	
	Attention Shifting intercept	-	
	Attention Focusing intercept	-	
	Effortful Control intercept	-	
	Inhibitory Control slope	-	
	Attention Shifting slope	-	
	Attention Focusing slope	-	
	Effortful Control slope	-	

Note. P = parent; T = Teacher.

All predictors but gender have been standardized, given that age, intercept factor scores, and slope factor scores had a different metric. The value of ' - ' denotes a regression coefficient shrunk to be zero.

PPM

Scenario 1: inhibitory control, attention shifting, and attention focusing develop as separated but correlated cognitive structures showing highly interdependent developmental processes

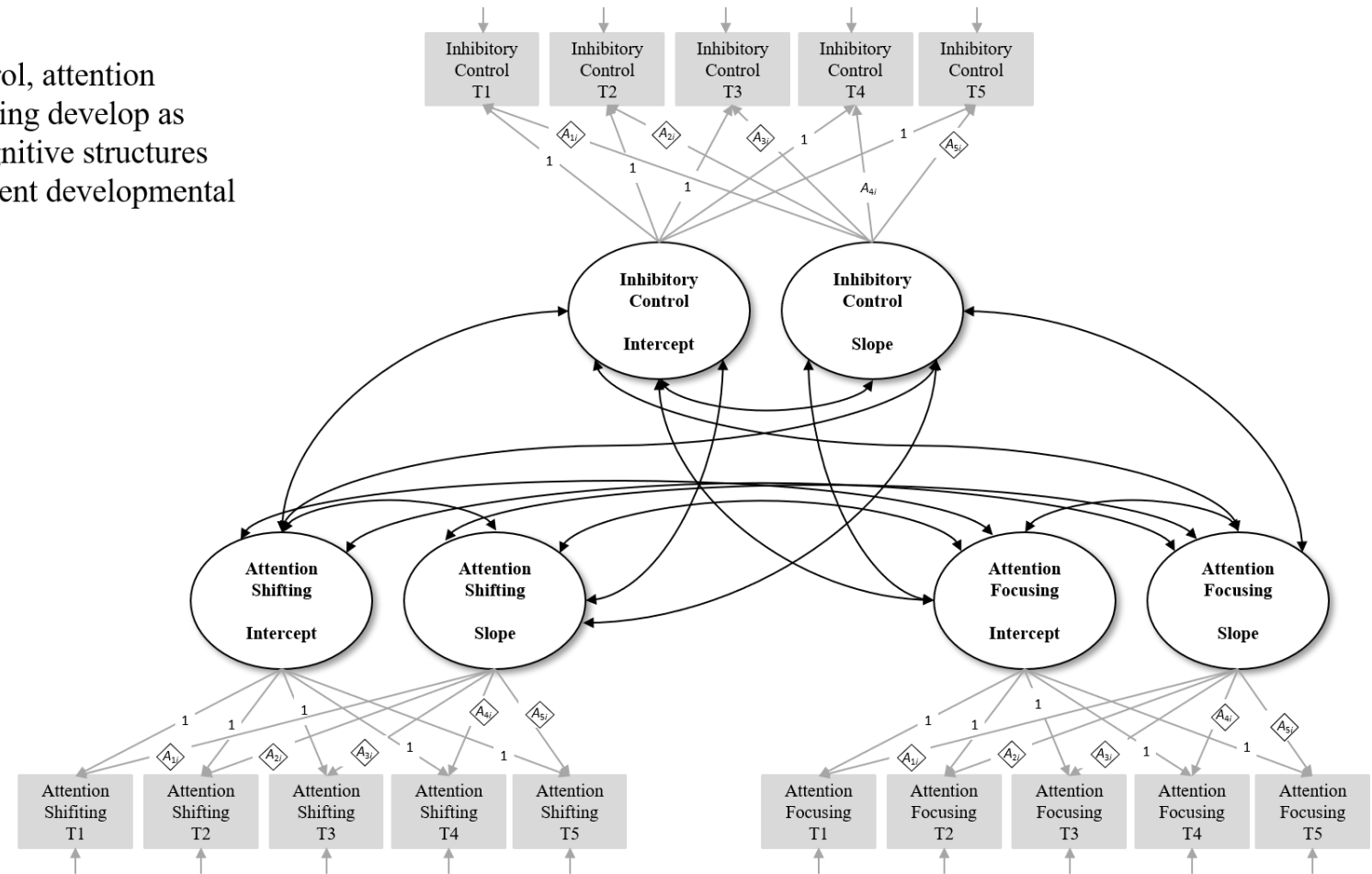


Figure 1. Parallel Process Model (PPM).

Note. Results are reported in Table 1. A_{1i} - A_{5i} within rhombuses represent the age A at which people i was at T1-T5.

Scenario 2: effortful control acts as a higher-order *common* developmental mechanism explaining the observed synchronism in the development of inhibitory control, attention shifting, and attention focusing

CFM

Scenario 3: inhibitory control, attention shifting, and attention focusing represent within-time temporal indicators of effortful control, that represents their common core

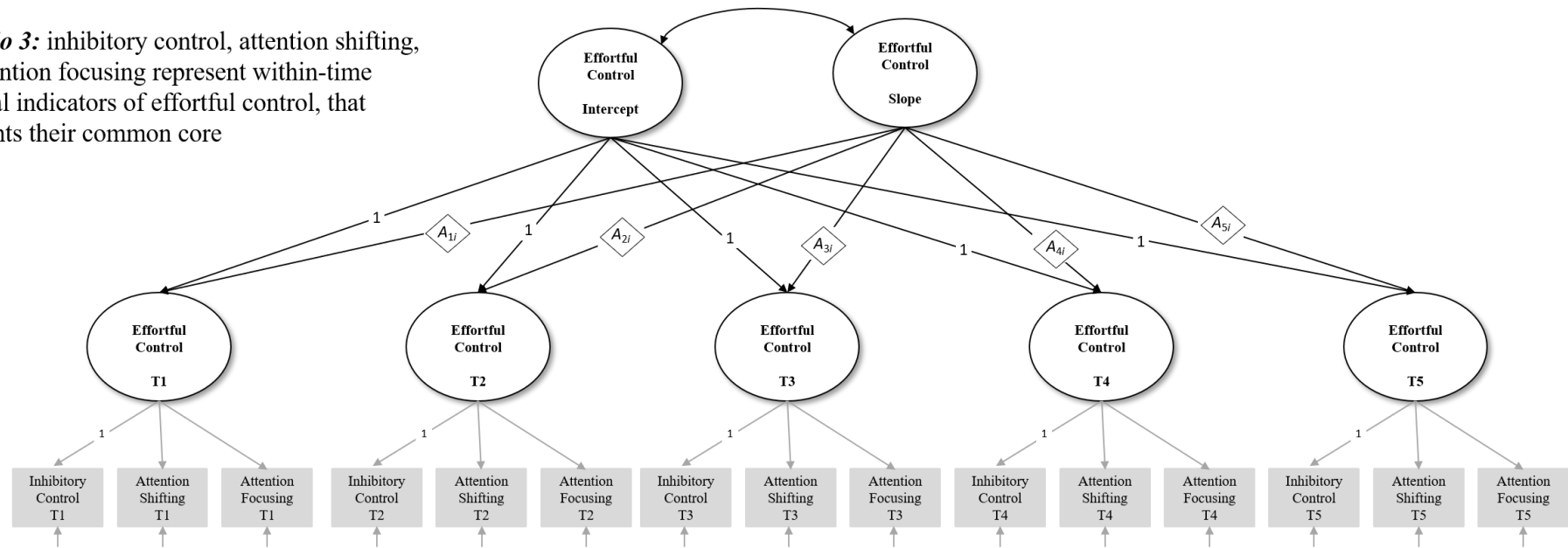


Figure 3. Curve of Factors Model (CFM).

Note. Results are reported in Table 1. A_{1i} - A_{5i} within rhombuses represent the age A at which people i was at T1-T5.

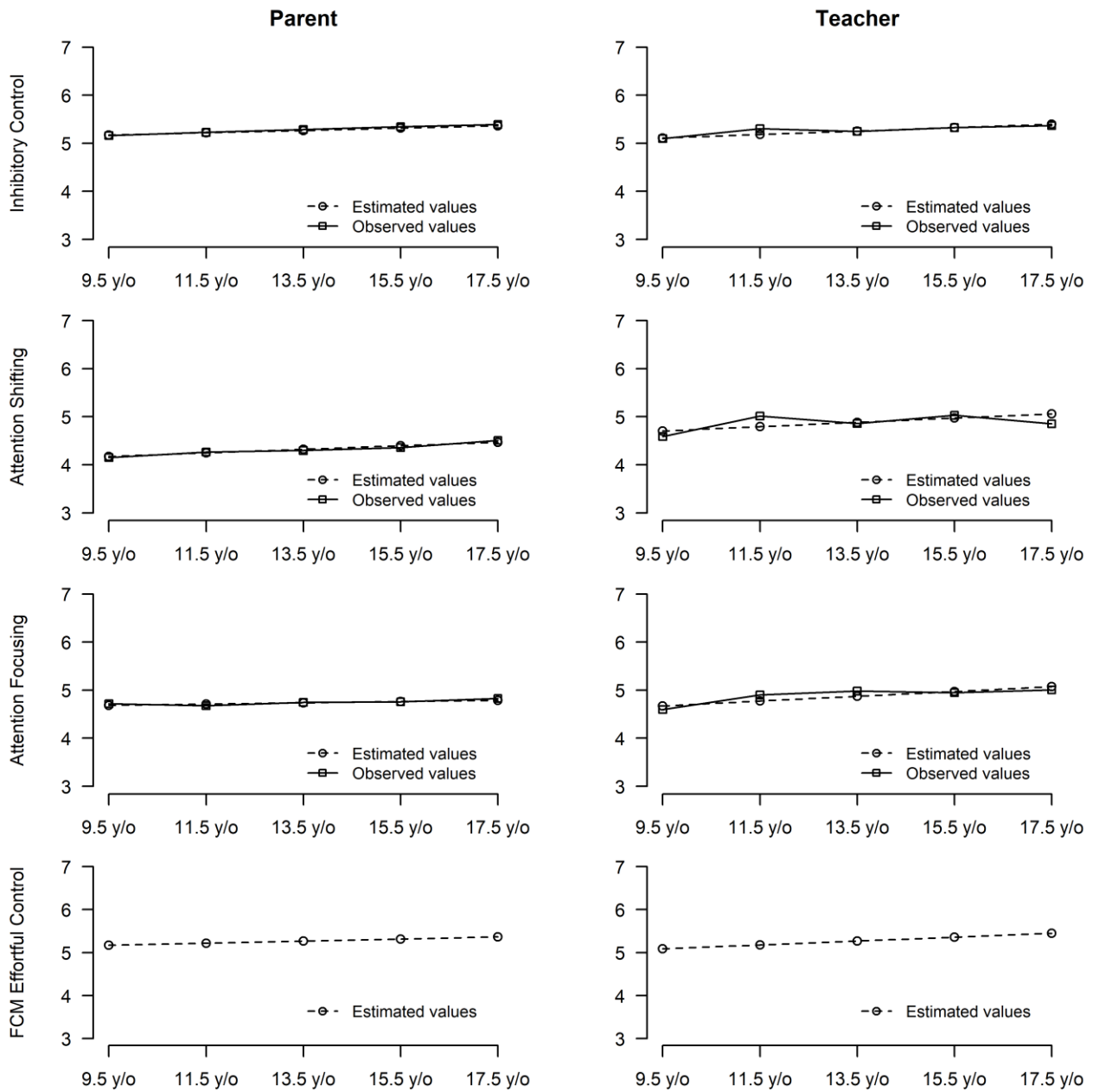


Figure 4. Trajectories of study variables from the best fitting models reported in Table 1. The ages on x axis refer to the (approximate) mean age at each wave. FCM = Factor of Curves Model.

Supplementary Materials

The Validity of the Higher-Order Structure of Effortful Control as Defined by Inhibitory Control,
Attention Shifting, and Focusing: A Longitudinal and Multi-Informant Study

Table S1*Zero-order Correlations and Descriptive Statistics*

	1)	2)	3)	4)	5)	6)	7)	8)	9)	10)	11)	12)	13)	14)	15)
1) IC T1	<i>.80/.89</i>	.75***	.78***	.69***	.63***	.62***	.63***	.53***	.53***	.38**	.46***	.48***	.40**	.24 ^{n.s.}	.43**
2) AS T1	.47***	<i>.74/.84</i>	.44***	.51***	.51***	.43***	.42***	.33***	.30**	.27*	.36***	.38***	.27*	.27*	.24*
3) AF T1	.69***	.23**	<i>.82/.90</i>	.54***	.46***	.57***	.55***	.47***	.58***	.49***	.44***	.52***	.19 ^{n.s.}	.19 ⁺	.30**
4) IC T2	.71***	.35***	.55***	<i>.85/.91</i>	.73***	.85***	.48***	.43***	.47***	.34**	.42***	.38***	.65***	.51***	.57***
5) AS T2	.39***	.66***	.23**	.44***	<i>.78/.86</i>	.57***	.52***	.37***	.46***	.29*	.38***	.31**	.57***	.37**	.42***
6) AF T2	.58***	.24**	.74***	.68***	.31***	<i>.84/.88</i>	.58***	.50***	.54***	.40**	.39***	.35**	.61***	.46***	.54***
7) IC T3	.63***	.31***	.46***	.75***	.36***	.53***	<i>.85/.88</i>	.74***	.79***	.38**	.32**	.31**	.53**	.56***	.35*
8) AS T3	.25**	.55***	.13 ^{n.s.}	.38***	.66***	.16*	.46***	<i>.80/.83</i>	.58***	.26*	.30**	.26**	.11 ^{n.s.}	.26*	.28*
9) AF T3	.55***	.21*	.63***	.53***	.25**	.72***	.64***	.25**	<i>.85/.91</i>	.28*	.28**	.29**	.29*	.29*	.34**
10) IC T4	.65***	.31***	.54***	.70***	.44***	.61***	.72***	.33***	.61***	<i>.84/.89</i>	.77***	.82***	.37*	.23 ^{n.s.}	.28 ⁺
11) AS T4	.43***	.54***	.23**	.43***	.72***	.23**	.44***	.65***	.25**	.61***	<i>.82/.87</i>	.73***	.36*	.35**	.33**
12) AF T4	.50***	.13 ^{n.s.}	.57***	.50***	.28**	.66***	.55***	.17*	.77***	.70***	.30***	<i>.87/.91</i>	.39**	.38**	.43***
13) IC T5	.55***	.33***	.42***	.62***	.29**	.52***	.68***	.29**	.56***	.76***	.43***	.55***	<i>.88/.77</i>	.69***	.77***
14) AS T5	.39***	.56***	.16 ⁺	.39***	.68***	.17***	.46***	.58***	.37***	.46***	.73***	.27**	.53***	<i>.81/.84</i>	.64***
15) AF T5	.42***	.21*	.50***	.37***	.14 ^{n.s.}	.57***	.52***	.16 ⁺	.68***	.50***	.18 ⁺	.69***	.72***	.35***	<i>.87/.90</i>
<i>M</i> _{Parent}	5.16	4.15	4.72	5.23	4.26	4.68	5.29	4.30	4.74	5.35	4.36	4.76	5.39	4.50	4.83
<i>SD</i> _{Parent}	0.83	0.79	0.92	0.87	0.87	0.95	0.87	0.85	1.00	0.88	0.95	1.08	0.93	0.90	1.07
<i>SK</i> _{Parent}	-0.48	0.12	-0.35	-0.63	-0.12	-0.40	-0.56	0.07	-0.36	-0.72	0.11	-0.53	-0.81	0.00	-0.61
<i>KU</i> _{Parent}	0.09	-0.14	-0.04	0.42	0.70	0.18	-0.07	0.15	-0.12	0.19	0.14	0.01	0.30	-0.35	0.13
<i>M</i> _{Teacher}	5.10	4.59	4.59	5.3	5.01	4.9	5.25	4.86	4.98	5.33	5.03	4.95	5.37	4.85	5.00
<i>SD</i> _{Teacher}	1.06	1.00	1.13	1.12	1.04	1.17	0.97	0.96	1.09	1.01	0.99	1.08	0.81	0.96	1.08
<i>SK</i> _{Teacher}	-0.54	-0.60	-0.47	-0.69	-0.58	-0.60	-0.80	-0.17	-0.92	-0.85	-0.19	-0.55	-0.59	-0.55	-0.66
<i>KU</i> _{Teacher}	-0.62	0.26	-0.45	-0.26	-0.22	-0.38	0.67	-0.48	0.44	0.55	-0.75	-0.46	0.69	0.00	-0.32

Note. Correlations below the diagonal refer to parent-rating, correlations above the diagonal refer to teacher-rating; along the diagonal (italicized) Cronbach's alpha were reported for parent- and teacher-report, respectively. IC = Inhibitory control; AS = Attention shifting; AF = Attention focusing; *M* = Mean; *SD* = Standard deviation; *SK* = Skewness; *KU* = Kurtosis.

^{n.s.} $p > .10$. ⁺ $p < .10$. * $p < .05$. ** $p < .01$. *** $p < .001$.

Table S2*Longitudinal Measurement Invariance Routine for Effortful Control (5 Time Points)*

Informant	Model	$\chi^2(df)$	CFI	TLI	RMSEA	AIC	$\Delta\chi^2(\Delta df)$	ΔCFI
P	Configural	87.149*(60)	0.985	0.973	0.049	4,362.84	-	-
	Metric	100.847**(68)	0.981	0.971	0.051	4,360.54	13.698(8) ⁺	.004
	Scalar	117.468**(76)	0.977	0.968	0.054	4,361.16	16.621(8)*	.004
T	Configural	85.014**(55)	0.975	0.953	0.055	4,105.863	-	-
	Metric	102.259**(63)	0.968	0.946	0.058	4,107.108	17.245*(8)	.007
	Scalar	122.357*** (71)	0.958	0.937	0.063	4,111.207	20.098*(8)	.010
	Scalar partial	114.139*** (70)	0.963	0.945	0.059	4,104.988	11.880^{n.s.}(7)	.005

Note. CFI = Comparative Fit Index; TLI = Tucker-Lewis Index; RMSEA = Root Mean Square Error of Approximation; AIC = Akaike's Information Criterion; P = Parent; T = Teacher.

In bold, the level of invariance obtained.

^{n.s.} $p > .10$. ⁺ $p < .10$. * $p < .05$. ** $p < .01$. *** $p < .001$

Table S3*Longitudinal Measurement Invariance Routine for First-Order Variables (5 Time Points)*

Informant	Variable	Invariance	#Parameters	χ^2	df	p	CFI	TLI	RMSEA	SRMR	Δ CFI
P	Inhibitory Control	Configural	85	68.937	50	.039	0.987	0.972	0.047	0.033	
		Metric	77	73.899	58	.078	0.989	0.980	0.040	0.045	-0.002
		Scalar	69	93.132	66	.016	0.981	0.970	0.049	0.043	0.008
	Attention Shifting	Configural	85	55.231	50	.284	0.996	0.991	0.025	0.040	
		Metric	77	60.383	58	.390	0.998	0.997	0.016	0.052	-0.002
		Scalar	69	75.269	66	.204	0.993	0.988	0.029	0.062	0.005
	Attention Focusing	Configural	85	56.712	50	.239	0.996	0.991	0.028	0.043	
		Metric	77	68.752	58	.158	0.993	0.988	0.033	0.055	0.003
		Scalar	69	135.971	66	.000	0.956	0.930	0.079	0.058	0.037
		Scalar - Partial	71	91.128	64	.015	0.983	0.972	0.050	0.059	0.010
T	Inhibitory Control	Configural	85	67.380	50	.051	0.985	0.968	0.047	0.062	
		Metric	77	72.064	58	.101	0.988	0.978	0.039	0.069	-0.003
		Scalar	69	84.556	66	.062	0.984	0.974	0.042	0.074	0.004
	Attention Shifting	Configural	85	56.627	50	.242	0.993	0.984	0.029	0.061	
		Metric	77	63.038	58	.303	0.994	0.990	0.023	0.072	-0.001
		Scalar	69	82.118	66	.087	0.982	0.971	0.039	0.070	0.012
	Attention Focusing	Scalar - Partial	70	70.202	65	.308	0.994	0.991	0.022	0.075	0.000
		Configural	85	67.435	50	.051	0.985	0.968	0.047	0.050	
		Metric	77	83.601	58	.016	0.978	0.960	0.053	0.085	0.007
		Scalar	69	101.884	66	.003	0.969	0.950	0.058	0.080	0.009

Note. Each latent variable was composed by three parcels.

P = Parent; T = Teacher; #Parameters = Number of Free Parameters; CFI = Confirmatory Fit Index; TLI = Tucker-Lewis Index; RMSEA = Root Mean Squared Error of Approximation; SRMR = Standardized Root Mean Square Residual.